Introduction to Machine Learning

NYU K12 STEM Education: Machine Learning

Department of Electrical and Computer Engineering,
NYU Tandon School of Engineering
Brooklyn, New York

Course Details

- Course Website
- Instructors:

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NYU

Outline

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The XOR Problem

- What is XOR?

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  The logical operation eXclusive-OR outptus 1 when inputs differ, and 0 otherwise.

Input A	Input B	Output
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Table 1: XOR Truth Table

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- Why is this a problem?

The XOR Problem

- Let’s see the decision boundary for AND and OR gates graphically

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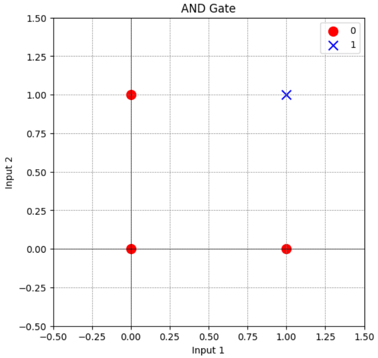

Figure 1: AND Gate

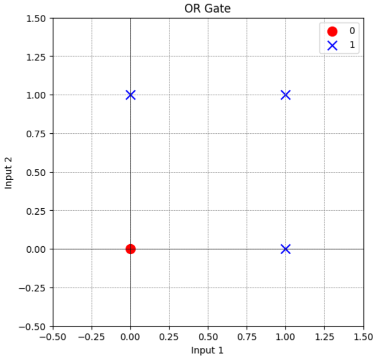

Figure 2: OR Gate

The XOR Problem

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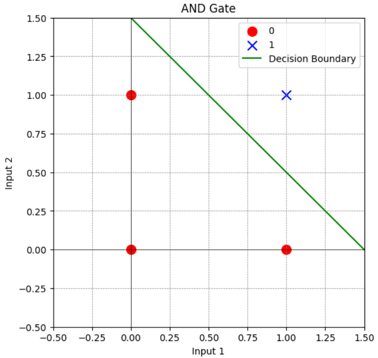

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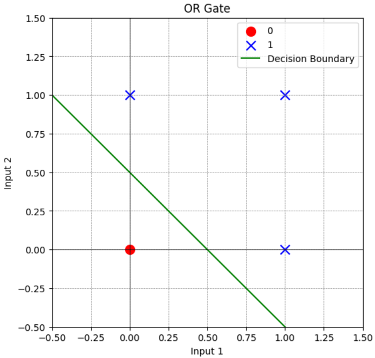

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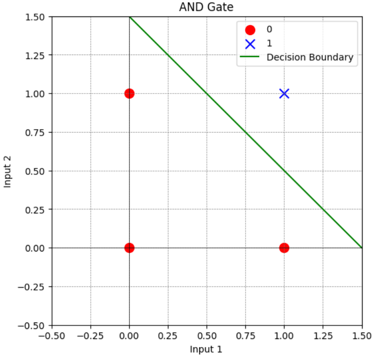

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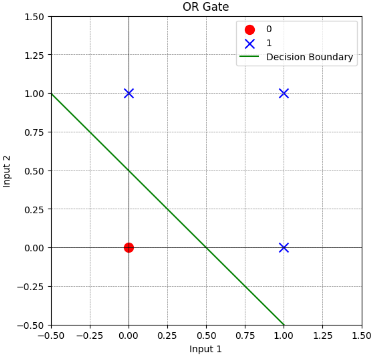

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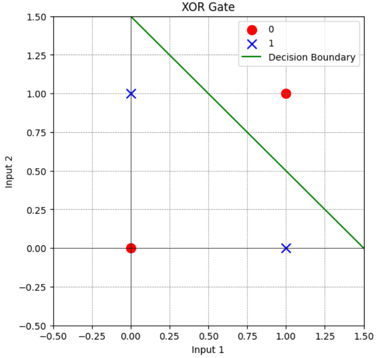


Figure 3: XOR Gate

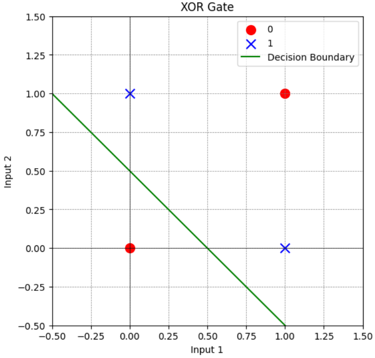


Figure 4: XOR Gate

Describing the General Limitation

- What about other distribution shapes?

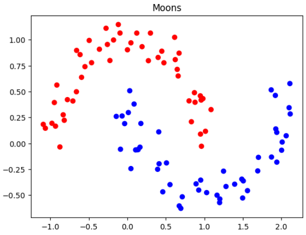
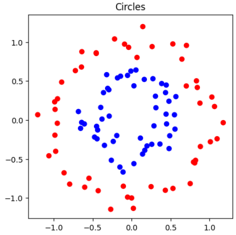


Figure 5: Moons



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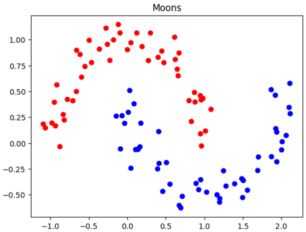

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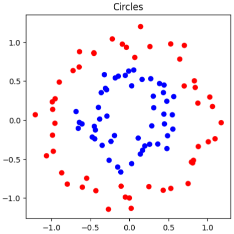

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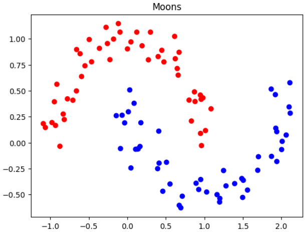

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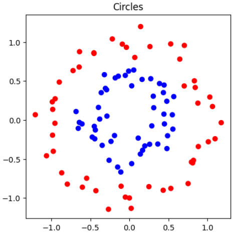

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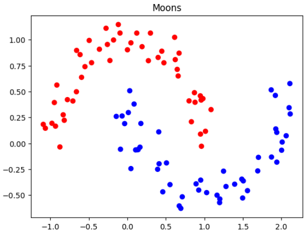

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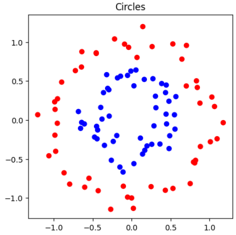

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- What can we do about this?
  - Non-Linear classifiers?

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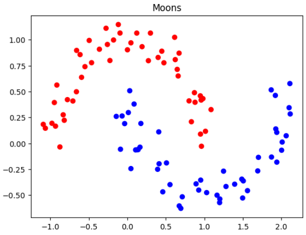

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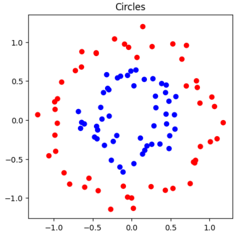

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- Can you suggest other shapes?
- What can we do about this?
  - Non-Linear classifiers?
  - Enter Neural Networks

Outline

1. Review
2. Limitations of Linear Classifiers
3. Neural Networks
4. Stochastic Gradient Descent
5. Overparameterized Models

Neurons

- What is a Neuron?

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  - Biological Neuron

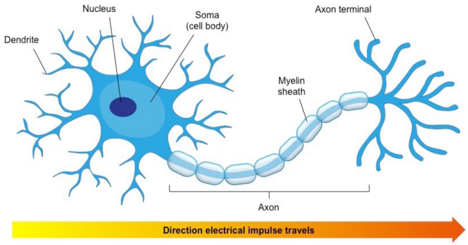
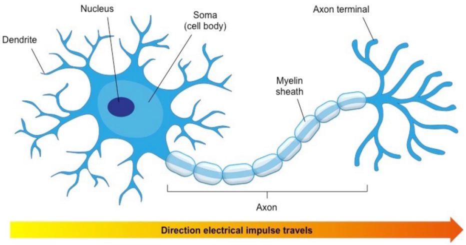


Figure 7: Biological Neuron
Source: Arizona State University

Neurons

- What is a Neuron?
- There are 2 definitions
  - Biological Neuron
  - Mathematical Neuron (Perceptron)



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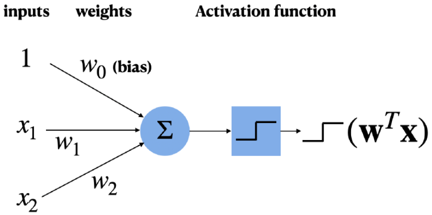
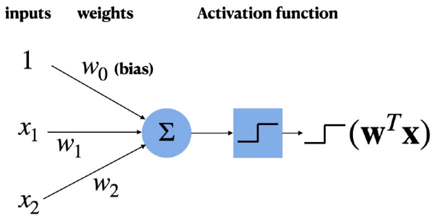


Figure 8: Mathematical Neuron

The Perceptron



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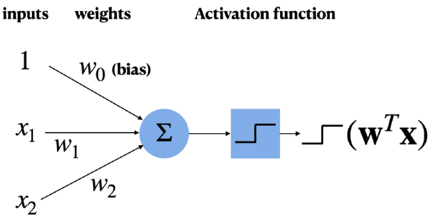
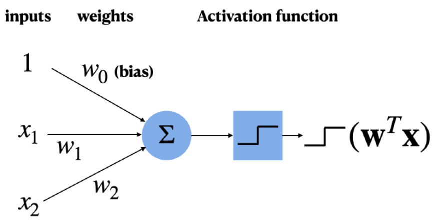


$$y = \varphi(\mathbf{W}^T \cdot \mathbf{X})$$

- Looks similar to Linear Classification!

The Perceptron



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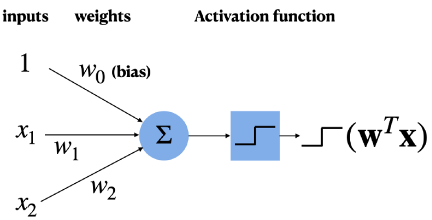

$$y = \varphi(\mathbf{W}^T \cdot \mathbf{X})$$

- Looks similar to Linear Classification!
- How is this supposed to revolutionize Machine Learning?
- HINT: How many neurons are in your brain?
  Does the Activation need to be Logistic/Sigmoid?

Neural Networks

- Solution 1: Connect many neurons together!
- This is the basic concept of a neural network
- Let's see a Multi-Layer Perceptron/Fully Connected Feed-Forward Network

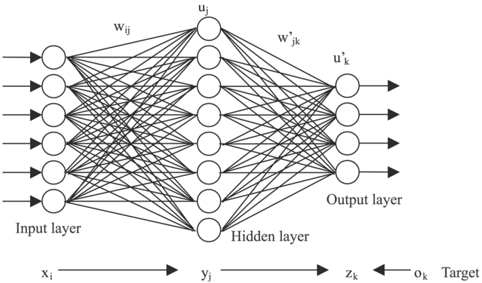

Figure 9: Neural Network

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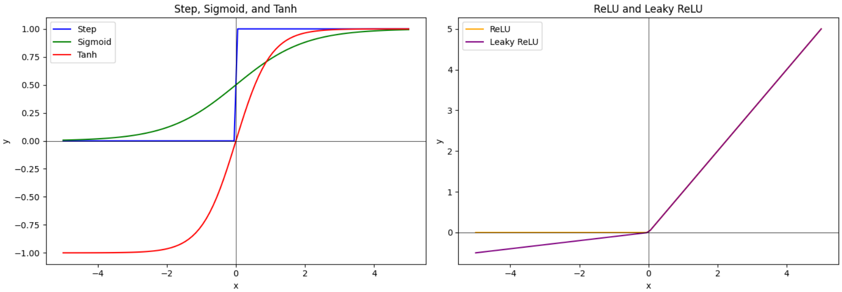

Figure 10: Different Activation Functions

Activation Functions

- Solution 2: Use different Activation Functions
- These have a significant impact on the behavior of a Neuron
- Softmax activation is particularly important!

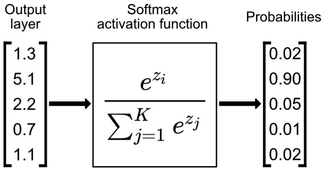

Figure 10: Softmax Activation
Source: Towards Data Science

MLP Example - 1

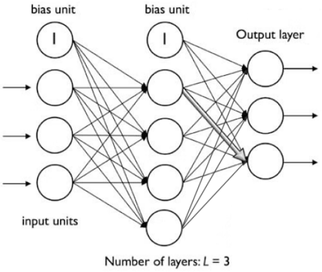

Figure 11: MLP Example 1

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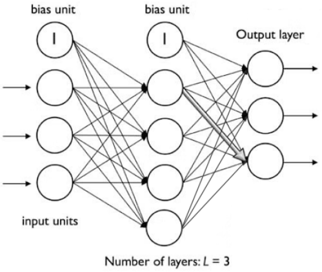

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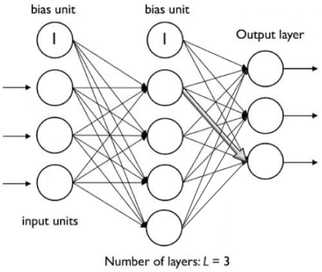

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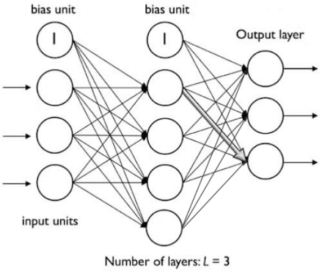

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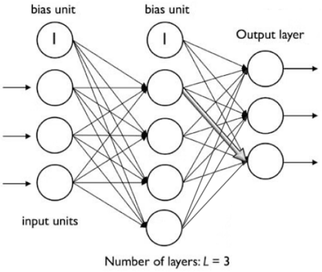

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MLP Example - 2

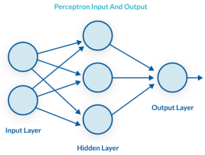

Figure 12: MLP Example 2

- What is the shape of input and output?
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MLP Example - 2

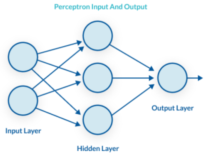

Figure 12: MLP Example 2

- What is the shape of input and output? (2, 1) and (1, 1)
- How many parameters does the model have? 13
- What activation functions would you use for output layer? Depends on the task

Deep Neural Networks

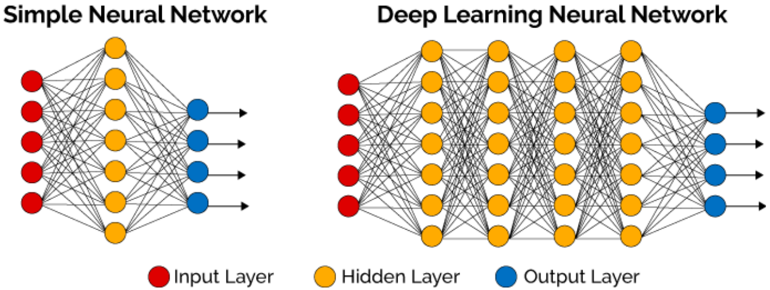

Figure 13: Simple vs Deep Networks

- There are many choices for the number of hidden layers and number of neurons per layer

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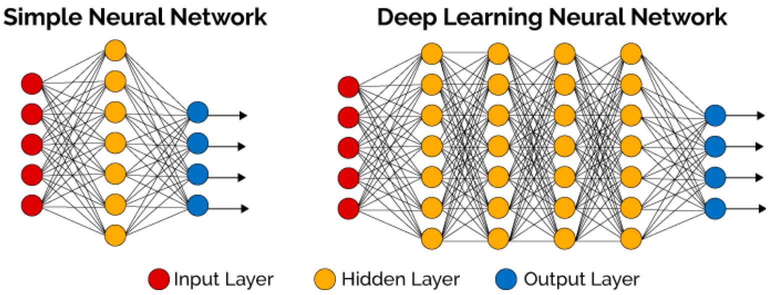

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- There are many choices for the number of hidden layers and number of neurons per layer
- MLPs can approximate almost any continuous function

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- For deep learning systems to perform well, we need large datasets -
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- Computational Challenges
  - Memory Limitation - GeForce RTX 2080 Ti has 11 GB memory, while ImageNet is about 300 GB.
  - Computation - Calculating gradients for the whole dataset is slow and done several times.

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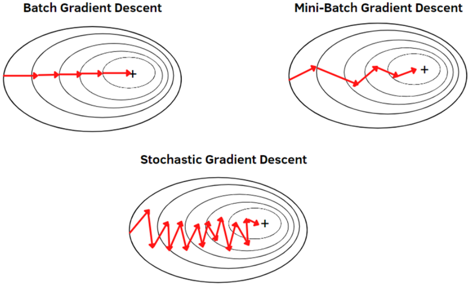
- But there is a tradeoff:
  - Each gradient is a bit noisy
  - More number of gradients need to be calculated

Stochastic Gradient Descent

- The descent ends up looking like this -



Stochastic Gradient Descent

- Consider a subset of the original dataset having size B
- The loss is then calculated as -

$$L(W) = \frac{1}{B}\sum_{i=1}^{B}(y_i - \hat{y}_i)^2$$

- The weight update rule then becomes -

$$W_{new} = W - \alpha \nabla L(W)$$

Stochastic Gradient Descent

- For different sizes of B, we have -
  - SGD: $B = 1$, and results in very noisy gradients
  - Mini-batch GD: B is small (typically 32, 64, 128 for images), and gradients have some noise
  - GD: $B = N$, and gradients have no noise

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  - GD: $B = N$, and gradients have no noise
- Even if feasible, GD is not a good idea. Noisy gradients can help
  - escape from local minima
  - escape from saddle points
  - improve generalization

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- Conventional wisdom: Such models overfit.
- It is not the case in practice!